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Nowcasting Indian GDP growth using a Dynamic Factor Model

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Abstract

In India, the first official estimate of quarterly GDP is released approximately 7-8 weeks after the end of the reference quarter. To provide an early estimate of current quarter GDP growth, we construct single-index dynamic factors (DFs) using a sequentially expanding list of 6, 9 and 12 high-frequency indicators. These indicators represent various sectors, display high contemporaneous correlation with GDP, and track GDP turning points well. While DF-6 includes domestic economic activity indicators, DF-9 combines indicators of trade and services and DF-12 adds financial indicators in the model. In addition to conventional economic activity indicators, we include a financial block in DF-12 to reflect the growing influence of financial sector on economic activity. DFs are estimated using a dynamic factor model which extracts a common trend underlying the high-frequency indicators. The extracted trend provides a real time assessment of the state of the economy and helps identify sectors contributing to economic fluctuations. Further, GDP nowcast using DFs show considerable gains in both in-sample and out-of-sample accuracy. In particular, our GDP growth nowcast is observed to closely track the recent slowdown in the Indian economy.

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Introduction

Real-time assessment of the state of the economy is a pre-requisite for taking appropriate policy measures. The effectiveness of policy-making depends on how well it uses all information available at any given time. Moreover, making use of the current flow of information is an essential ingredient in formulating a forward-looking policy. Today, in a dynamic environment, data driven policy-making is considered both practical and desirable. This is all the more important because of significant lags in official data releases of key macro variables such as GDP. Emerging market economies face serious problems of data lags, gaps and revisions which hamstring optimal policy decisions.

A core concern in policy-making is identifying the signs of expansions and contractions in economic activity. At any point, diverse economic indicators may indicate varied trends in activity. Therefore, combining all of these together in an appropriate way to arrive at the underlying (or unobserved) trend has traditionally occupied the attention of both governments and businesses. Traditionally, a lot of work was done in the National Bureau of Economic Research and the Department of Commerce in the US on identifying business cycles using multiple indicators. Often, their analysis relied on prior beliefs and judgement. Later, academic research contributed by making the analysis more formal and mathematically precise (see Stock and Watson, 1989). Presently, this whole exercise displays a mix of both sound conceptual framework, careful inference and judgement.

There exists a two-pronged challenge in assessing the underlying state of the economy using high frequency indicators. The first one is the choice of appropriate indicators from a large set of potential indicators. The second challenge is associated with signal extraction from the chosen indicators. This is because individual indicators may reflect short-term idiosyncrasy rather than an underlying general trend. Researchers look at a variety of indicators relating to different aspects of the economy – production, income, sales and employment – together to assess the underlying state of the economy. The consensus trend emanating from all these indicators suggests recessions or expansions (or equivalently slowdowns and accelerations) in economic activity. The dynamic factor tries to address the challenge of signal extraction by identifying the general (or common) trend underlying several activity indicators.

To address the first challenge of identifying appropriate indicators, our approach is to weigh indicators based on their information content about the

dynamics of GDP. We identify a pool of relevant indicators based on (1) contemporaneous correlations between indicators and GDP; and (2) explanatory power of the indicators around GDP turning points. Based on these two criteria, we choose a set of twelve indicators which includes index of industrial production – consumer goods and core sectors, automobile sales, non-oil non-gold imports, exports, rail freight, air cargo, foreign tourist inflows, government tax receipts, Sensex, Nominal Effective Exchange Rate (NEER) and bank credit. Despite following an independent variable selection approach, our choice of indicators is similar but not the same as Stock and Watson (1989) which used index of industrial production, real personal income, real manufacturing and trade sales, and employee-hours in non-agricultural establishments to construct a Coincident Economic Indicator. One reason for deviating from Stock and Watson (1989) is that in emerging markets such as India, indicators on employment and income are difficult to obtain at high frequency. Therefore, researchers have used suitable proxy variables. The second reason for deviation is the unavailability of data on such indicators for a long period. On the whole, our choice of indicators represents real, external and financial sectors which are used to extract the common underlying trend using a single-index dynamic factor model. We call the estimated indices DF-6, DF-9, and DF-12, based on a sequentially expanding list of 6, 9 and 12 high-frequency indicators, respectively.

Given the lags in the release of official GDP, the estimated DFs are used to obtain the current quarter nowcast of GDP. Broadly, the nowcast exercise is an extension of the bridge type regressions that relate GDP to quarterly aggregates of relevant economic indicators. However, we rely on a parsimonious autoregressive model of GDP augmented by monthly DFs. While tracking the actual GDP dynamics closely in the sample, our modelling approach also shows considerable gains in terms of out-of-sample performance.

The rest of the paper is organised as follows. Section II provides a comprehensive review of the literature on high-frequency indicators and nowcasting, including cross-country studies as well as the literature specific to India. Section III briefly describes the data used for constructing DFs. Section IV presents the methodology and empirical results on indicator selection, estimation of a dynamic factor model, nowcasting GDP and performance evaluation of our models. We put our concluding remarks in section V. Annexes contain technical details.

II. Literature

Nowcasting involves an exercise of predicting the present, the very near future, and the very recent past - that makes it more effective in shorter horizon

forecasting (Banbura, Gianonne and Reichlin, 2010). A set of high-frequency indicators is commonly used in GDP nowcasting exercise. Perhaps, the first use of such indicators is found in Burns and Mitchell (1946), which popularized the study of business cycles, and that eventually led to the creation of the composite index of coincident indicators. The methodology has gradually been refined over time and a breakthrough came in the Stock and Watson's (1989) seminal work on estimating a single-index dynamic factor model (DFM). More recently, Giannone, Reichlin and Small (2008) have pioneered the usage of DFM based on a large number of high-frequency indicators and found that the nowcasts have outperformed standard univariate models like random-walk and autoregressive (AR) models. Generally, a wide variety of high-frequency indicators are actively monitored in gauging the health of an economy. The indicators used are in-sync with the current economic cycle and primarily represent six blocks which include: *(*a) industry and construction, (b) personal income (or consumption), (c) payroll employment (d) services (e) external sector, and (f) price. These indicators are chosen not merely because of their correlation with GDP, but also because they contain timely information about the target variable.

Depending on countries and sample periods, various researchers have also included miscellaneous economic activity indicators (*e.g.,* air cargo, rail freight, and port traffic and uncertainty / volatility indices). Though, most of the financial sector variables (*e.g.,* money supply, currency with public, credit, equity indices and bond indices) are generally classified as lead indicators, some of the studies have incorporated them in GDP nowcasting and documented improvement in their nowcasting performances (Annex Tables I and II report the details). Some researchers have included financial conditions indices (a linear combination of risk spread, asset returns and volatility) to model the risk to output growth one year into the future (IMF, Global financial Stability Report, October 2017).

II.1 Cross-country nowcasting models

Modern macroeconomic literature emphasizes the role of forward looking assessment of growth and inflation by central banks in policy formulation. Globally, central banks and their monetary policy committees (MPCs) rely on high-frequency economic indicators for an assessment of the current state of the economy. For instance, Bank of England's MPC uses such a model-based nowcast. Similarly, the Federal Reserve Bank of Atlanta (FRBA)[2] and the Federal Reserve Bank of New York (FRBNY)[3] publish their own model-based nowcasts in addition to the routine

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[2] GDPNow forecasting model by FRBA does a "nowcast" of the official estimate prior to its release by estimating GDP growth using a methodology similar to the one used by the U.S. Bureau of Economic Analysis.

[3] The FRBNY nowcast model produces forecasts of GDP growth for all variables taking into account their dynamic interactions.

forecast produced in the bank. The European Central Bank[4] also consults a DFM-based nowcasting model. Other central banks such as Norges Bank[5] uses nowcasting models of GDP for its policy decisions.

Outside the ambit of central banks, several country-specific GDP nowcasts have evolved over time. Among the advanced economics (AEs), Kumar (2013) constructed a high-frequency real activity indicator that tracked economic activity in Canada reasonably well. The indicator is obtained as an unobserved common factor capturing the co-movements in real macroeconomic variables. Similarly, Chikamatsu *et al.* (2018) produced nowcasts of quarterly GDP estimates for Japan by adopting a bridge equation approach. The bridge equation links the low-frequency target variable with the high-frequency indicators. Annex Table I provides an exhaustive list of variables used by the authors.

While DFM based nowcasting models have been adopted for a long time across advanced economies, emerging market economies (EMEs) have started exploring the usefulness of such models only recently. For instance, Luciani *et al.* (2015) used high frequency indicators (*e.g.* cement, PMI-manufacturing, consumer confidence, auto sales, etc.) for Indonesia in estimating a dynamic factor and then used the same to nowcast GDP growth in an autoregressive, bridge-equation framework. Caruso (2015) used the Maximum Likelihood estimation in an expectation-maximization (EM) algorithm for constructing an economic activity index for Mexico. The EM algorithm is useful in analyzing non-synchronous data releases that are often observed in EMEs.

II.2 Nowcasting Indian GDP

Among the emerging markets, India has a reasonably long history of research in tracking and nowcasting GDP. Early works in this domain include Dua and Banerji (2001), and Technical Advisory Group constituted by the Reserve Bank of India (2007). Dua and Banerji (1999) published an index of monthly coincident indicators to help ascertain the timing of recession and expansion of economic activity based on a set of objective indicators that are synchronous with cyclical fluctuations in growth. Some of the indicators (*e.g.* monthly unemployment numbers published in the Monthly Abstract of Statistics) are not published anymore. However, we report an update of this monthly index, using available data and proxy variables, in the Annex Note I. Along similar lines, Reserve Bank of India (2007) published a set of indicators including Composite Index of Leading Indicators (CILI) and Composite Index of

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[4] The European Central Bank models the monthly data as a parametric dynamic factor model cast in a state-space representation against the quarterly GDP.

[5] Norges Bank analyzes unstructured textual information of a business newspaper to decompose daily news topics and nowcast quarterly GDP growth for policy rate decisions.

Coincidental Indicators (CICI) based on a detailed empirical exercise using growth cycle and growth rate cycle methodologies. CILI and CICI were mainly based on principal component analysis (PCA) with sample data spanning from April 1990 to March 2006.

Recent academic research, such as Dalhaus *et al.* (2017) and Bragoli and Fosten (2017) adopted a standard dynamic factor model (DFM) framework for GDP growth nowcasting. Both these studies attempted to extract monthly unobserved common factor from a set of monthly indicators. Following factor extraction, monthly projection of GDP growth is estimated based on the dynamics of the common factor. The indicators used in these studies are summarized in Annex Table II. Dua and Sharma (2016) used a univariate Markov regime switching model to characterize growth cycle phenomena and distinct economic regimes for India and compared them with the US, UK, Germany and Japan. In addition to academia and central banks, market research organizations, think-tanks, and professional economists have estimated and published indices based on high-frequency indicators and used them to nowcast India's GDP. For instance, Rabobank[6] uses different models to nowcast India's GDP growth that include Bayesian VAR (BVAR), OLS and a combined model, which help in deriving the underlying contribution of high-frequency indicators in GDP growth forecasts. Besides economic indicators, Rabobank also includes financial indicators such as monetary base (M_0), volatility index (VIX), BSE-500 index and Sensex.

National Institute of Public Finance and Policy (NIPFP) estimated common factors using PCA and then used three different variants of bridge equation models. The NIPFP working paper (Bhattacharya *et al.,* 2010) used variables from several sectors of the economy that included industrial production, construction, services and financial sectors and documented that the empirical strategy outperformed the benchmark AR models. An NCAER working paper (Bhadury *et al.,* 2018) presented a new framework to nowcast India's GVA using information of mixed da, 2018ta frequencies and adding evening-hour luminosity information to capture economic activity of informal sectors in India.

In India, professional economists (economists with banks, brokerage houses and think tanks) also regularly nowcast GDP using proprietary models. Some of the GDP nowcasts by these economists are also published by the Bloomberg[7], however, their exact nowcasting methodologies are not in the public domain. Bloomberg also publishes its *Monthly GDP tracker* to provide an advance estimate of the current

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[6] Rabobank combines predictions from Bayesian Vector Autoregressive (BVAR) model and an Ordinary Least Square (OLS) model for GDP forecasts. Link: https://economics.rabobank.com/publications/2019/february/nowcasting-the-indian-economy/

quarter economic activity in India. The *Monthly GDP tracker* is constructed by applying weights to the monthly activity indicators, such as agricultural trade balance, real currency demand, industrial production, *etc.* (details in Annex Note I) and the weight assigned to each monthly indicator is the inverse of the standard deviation of the respective indicator.

To summarize, the use of economic activity indicators in GDP nowcast has a long history in advanced economies and still being actively used in monetary policy-making by the central banks. Though there have been debates relating to inclusion of high frequency variables, their lead, lag or cotemporaneous characteristics, nowcast exercise has moved on by including new blocks of variables with an objective to improve nowcast performance. The application of high-frequency variables in GDP nowcasting is relatively new in emerging market economies and have been challenged by small sample size, non-synchronous data releases and varying data lags. However, considering its importance in policymaking, economists have been striving with new empirical strategies to bridge this gap and use such indicators as an active policy tool.

III. Data

Our attempt here is to construct an index for the Indian economy that tracks business cycle reasonably well. The first best is always the quarterly estimates of GDP at constant prices which is published by the Central Statistical Office (CSO)[8] with a lag of two months. Given the delay in data release, we use dynamic factors in providing the current-quarter nowcast of GDP, our target variable. The indicators used in the construction of DF-6, DF-9 and DF-12 represent all relevant sectors of the Indian economy. Data published on a monthly frequency is exploited to construct the DFs and are sourced from the CEIC database.[9]

The high-frequency monthly series associated with industry and construction block is IIP-core industries. Personal income and consumption block is represented by indicators such as IIP-consumer goods and auto sales. Exports, non-oil and non-gold imports and foreign tourist arrivals represent the external sector block. Rail freight, air cargo and government revenue receipts represent services and miscellaneous economic activity, respectively. The above indicators are included in DF-6 and DF-9. In addition, we develop a DF-12 that adds a credit and finance block

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[7] Bloomberg tracks real time GDP data using a weighted methodology to nowcast GDP from high frequency volume based economic indicators.

[8] The Ministry of Statistics and Programme Implementation has decided to merge the CSO and National Sample Survey Office (NSSO) into National Statistical Office (NSO).

[9] CEIC is a data aggregator that collects data from different ministries, government documents and other data originators.

by including non-food credit, NEER and Sensex. Though in the literature, equity index and credit, in some instances, have been classified as lead indicators, we explain the rationale for including these variables in the DF-12 in the discussion on variable selection.

At this juncture, it might be important to mention that the GDP series has been revised and rebased in India from time to time. For instance, on November 28, 2018 the Ministry of Statistics and Programme Implementation released the annual back series of data beginning 2004-05 (at 2011-12 prices). As per the new series, GDP growth has been revised downward during 2004-05 to 2011-12 compared to the earlier 2004-05 series. However, the Ministry has not separately released the back series of the quarterly data. Therefore, we rebase the older 2004-05 and 1999-2000 series to match the 2011-12 quarterly data.[10]

IV. Methodology and Empirical Results

The empirical exercise entails variable selection, standardization, smoothing and appropriately combining these transformed variables into an index. This index is then used for GDP nowcasting. We approach the above empirical exercise in four sequential stages in the following manner.

IV.1 Variable Selection

Variable selection is perhaps the most crucial part of the exercise. Our aim is to include indicators that capture the pronounced and persistent movements in economic activity. We look at the availability of high frequency data for over sufficiently long period and the literature that is particularly relevant for India *e.g.* Dua and Banerji (2000), and Reserve Bank of India (2007). We begin with an extensive survey of the international literature relating to high-frequency indicators that are used in producing real time assessment of GDP growth (see Annex Tables I and II). Based on the review of literature, we shortlist 28 high-frequency indicators for the Indian economy. These indicators represent all major sectors in the economy, such as industry and construction, personal income and consumption, employment, services, external sector, prices, credit and finance, and miscellaneous economic activity. The summary Table 1(a) below reports the indicators and the sectors that they represent in the economy.

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[10] As a robustness exercise, we also use the downwardly revised Y-o-Y growth of the new back series. This, however, does not change our estimates significantly.

We attempt to nowcast GDP using available high frequency indicators for the reference quarter. In doing so, we focus on those high-frequency indicators that will capture the GDP dynamics but would avoid overfitting. Therefore, while we start with an exhaustive list of high-frequency indicators including those used by National Statistical Office (NSO), we finally select 6, 9 and 12 indicators representing all major sectors in the economy. Based on the nowcasting literature, the selected indicators represent production, income, consumption and sales activities. Thus, they represent a mix of both expenditure and production side. The summary Table 1(b) below reports some of the key indicators used by NSO to provide the first advance estimates of quarterly GVA. Our list of indicators includes many of those used by NSO for GVA compilation. Additionally, we take into consideration indicators that proxy income/consumption, employment, prices, and external sector.

Table 1(a): Summary of selected indicators based on the review of nowcasting literature

Industry & construction	Income/ Consumption	Employ-ment	Services	External Sector	Prices	Misc. Eco. Activity	Credit & Finance
IIP - Core*	IIP - Consumer Goods*	Agricul-tural Wages	Air Cargo*	Non-Oil, Non-Gold Imports*	CPI - Industrial Workers	Govt. Total Receipts*	Bank Credit to Commercial Sector*
Oil Consumption (Petrol & HSD)	Automobile Sales - Total*		Rail Freight*	Exports*			Sensex*
Power Demand	Automobile Sales - Commercial		Air Passen-ger	Foreign Tourist Arrivals*			Treasury Bill 91 Day Yield
Steel Production	Automobile Sales - Passenger		Rail Passen-ger	NEER*			
Cement Production				Forex Reserves			
				CRB Commodity Index			
				Crude Prices (Indian Basket)			
				OECD Industrial Production			
				CBOE Volatility Index (VIX)			

*: These indicators are used in the construction of DFs.

Table 1(b): Key indicators used by the NSO
in providing first advance estimate of GVA

Industry and construction	Income/Consumption	Employment	Services	External Sector	Prices	Misc. Economic Activity	Credit & Finance
IIP-Mining			Air Cargo			Growth in Sales tax	Aggregate Bank Deposits
IIP-Manufacturing			Cargo via Sea port			Govt. Expenditure	Bank Credits
IIP-Electricity			Air Passenger				
Production of Coal, Crude Oil & Natural Gas			Rail Freight				
Cement Production			Rail Passenger				
Steel Consumption							

Source: CSO press releases.

Our second round of indicator screening is based on the dynamic correlation between indicators and the target variable i.e., GDP. In addition to examining the correlation of indicators with the target variable over the full sample, we also pay special attention to dynamics around turning points in GDP. In emerging markets including India, GDP dynamics is seen to be more volatile displaying significant accelerations and decelerations in growth in quick succession. Therefore, a desirable feature of indicator selection would be to capture such dynamics. To achieve this, we use a forward step-wise and Lasso selection procedure to identify the set of 12 high-frequency indicators that are relevant around turning points in India's GDP.

Dynamic Correlation

We look at the correlation of Q-o-Q seasonally adjusted annualized growth of the variables with our target variable, GDP. The dynamic correlation analysis is carried out over 2003:Q1 to 2019:Q1 with around 65 observations at different leads and lags of GDP. We have identified variables as Cotemporaneous ('C'), Leading ('L+') and Lagging ('L-') indicators depending on their contemporaneous, future and past correlations, respectively with GDP. These correlation coefficients and their statistical significance are presented in the Annex Table III. Among the economic indicators, the highest contemporaneous correlation with GDP is observed for Sensex, IIP-consumer goods and air cargo. Finally, a few indicators such as IIP-core, commercial automobile sales and forex reserves display both cotemporaneous and leading properties in terms of their correlations with contemporaneous and future GDP. The summary Table 1(c) below reports the dynamic correlation coefficients for the shortlisted high-frequency indicators.

Table 1(c): Summary of selected variables using Dynamic Correlation

Indicators	GDP$_{(t-1)}$	GDP$_{(t)}$	GDP$_{(t+1)}$	Indicator Type
Air Cargo	0.17	0.37*	0.27*	C
Auto Total	0.17	0.25*	0.24*	C
Bank Credit	0.11	0.08	-0.09	X
Exports	0.31*	0.35*	-0.02	C
Foreign Tourist	0.19	0.36*	0.12	C
Govt Receipts	0.21*	0.10	-0.01	L-
IIP Consumer	0.20*	0.54*	-0.01	C
IIP Core	0.25*	0.20*	0.28*	L-/C/L+
NEER	0.14	0.24*	0.15	C
NONG Imports	0.33*	0.19	-0.02	L-
Rail Freight	0.20*	0.17	0.15	L-
Sensex	0.25*	0.52*	0.23*	C

Note: NONG: Non-oil-non-gold imports; NEER: Nominal Effective Exchange Rate
*: Indicates 5 per cent level of significance; C: Cotemporaneous; L+: Leading & L-: Lagging indicator.
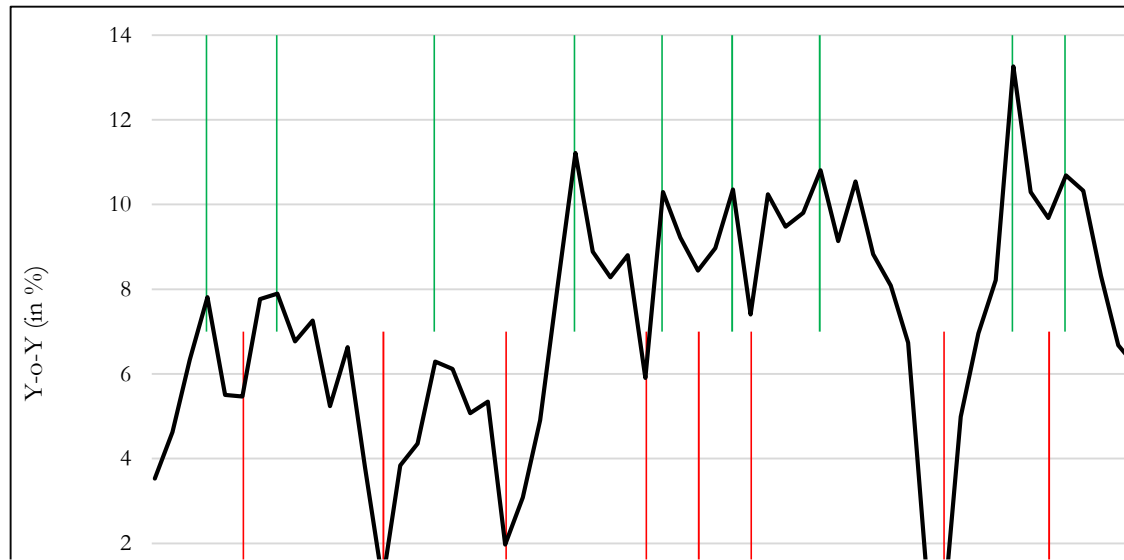
Next, we use the forward step-wise selection, followed by the Lasso procedure to identify indicators that are relevant around turning points in GDP. The notion of using indicators to discern business cycle peaks and troughs is not new in the growth literature. Our aim is similar in spirit to that of Moore (1950) i.e., identify turning points in India's business cycle using high-frequency indicators. Such indicators can provide a sense of recession risks, and enable policymakers and business-decision makers to have a better-informed analysis of the economic situation. OECD has a methodology to identify turning points using Composite Leading Indicators (CLI). CLI is periodically measured by OECD for 33 member countries and 6 non-member countries including Brazil, China, India, Indonesia, Russia and South Africa[11].

Unlike several advanced and emerging market economies, Indian economy has not experienced economic contractions or recessions in the last few decades. Instead, it is characterised by accelerations and slowdowns in growth rate around a (time-varying) trend level of GDP growth (see Acharya *et al.,* 2020). Accordingly, we identify turning points in India, keeping in mind the "growth rate cycle" instead of "growth cycle". Our approach of capturing the "growth rate cycle" helps us identify more turning points for India compared to the OCED approach because it is based on identifying short-duration cycles to capture volatility in GDP instead of relying only

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[11] OECD uses the turning point detection algorithm, which is a simplified version of the original Bry and Boschan (B&B) routine. B&B routine parses local minima and maxima in the cycle series and applies the censor rules to guarantee alternating peaks and troughs. OECD's CLI based approach has identified 10 such turning points for the Indian economy with +1 set for a peak and -1 set for a trough. The reference chronology of the turning points are as follows: trough in October-1997, peak in December-1999, trough in January-2003, peak in September-2007, trough in March-2009, peak in December-2010, trough in July-2013, peak in March-2016, trough in July-2017, and peak in May-2018.

on long-duration cycles. Chart 1 below plots the real GDP growth and its turning points for India.

Chart 1: Turning points in the business cycle

Forward Step-wise Selection

The forward step-wise selection procedure is a computationally efficient alternative which sequentially add candidate variables to assess their predictive power around the turning points in GDP. In particular, at each step the variable that gives the highest incremental improvement (to the fit) is included in the model. The summary Table 1(c) below provides a relative ranking of the variables in terms of their relevance around turning points. In terms of relative ranking, IIP-Consumer goods, auto sales and NEER have highest relevance around the turning points in GDP.

Lasso

Lasso shrinks the coefficient estimates towards zero by forcing some of the coefficient estimates to be exactly equal to zero when the tuning parameter, λ, is set at a sufficiently large value. Thus, the lasso technique performs variable selection much like the forward step-wise selection procedure. The lasso coefficient β_{λ}^{L} minimizes the quantity and $|\beta_j|$ is the lasso penalty

$$\sum_{i=1}^{n}(y_i - \beta_0 - \sum_{j=1}^{p}\beta_j x_{ij})^2 + \lambda\sum_{j=1}^{p}|\beta_j| \quad = \quad RSS + \lambda\sum_{j=1}^{p}|\beta_j|$$

Lasso yields a sparse model, which involves a subset of the variables that make model interpretation easier. Based on the Lasso criterion, a list of indicators that are found to be relevant around turning points in the GDP growth cycles is

reported in the summary Table 1(c). Lasso technique suggests that indicators such as IIP-consumer goods, auto sales, NEER, IIP-core, rail freight, Sensex and exports are relevant for India's GDP turning points. Interestingly, the forward step-wise selection method assigns the highest rank to the same set of indicators, thereby confirming the relevance of such indicators around turning points.

**Table 1 (d): Summary of selected variables using Lasso
and Forward Step-wise Selection**

Indicator	Turning point correlation	Forward Step-wise Selection	Lasso#
Auto Total	0.55*	2	Y
NEER	0.55*	3	Y
IIP Core	0.58*	4	Y
Rail Freight	0.24*	5	Y
Sensex	0.65*	6	Y
Exports	0.65*	7	Y
Air Cargo	0.57*	8	N
NONG Imports	0.46*	9	N
Bank Credit	0.11	10	N
Govt Receipts	0.32*	11	N
Foreign Tourist	0.57*	12	N

*: Indicates 5 per cent level of significance; # Y: Relevant indicators around turning points in GDP using Lasso, N: Indicators that are not relevant around turning points in GDP.

To summarize, our main objective is to construct an economic activity index for India based on high-frequency indicators that co-move strongly with the target variable. Our first and second rounds of screening are based on the review of literature and dynamic correlations between high-frequency indicators and GDP, respectively. Further, to refine relevant indicators around turning points, we look at the forward step-wise selection and Lasso criteria. In the next section, we construct a battery of economic activity indices that include a DF-6 model covering exclusively domestic economic activity indicators, a DF-9 model incorporating trade and services sector, and finally a DF-12 which incorporates financial variables. Furthermore, we equally consider experts' views, literature and judgement in identifying and grouping variables.

IV. 2 Dynamic Factor Model

After selecting the relevant variables to be incorporated in our model, we proceed to estimate a single factor representing the common trend underlying these variables. The single factor is obtained by estimating a dynamic factor model (DFM), a procedure widely popular in the recent literature. For analytical clarity, we sequentially estimate 6-indicators, 9-indicators and 12-indicators DFMs.

Our dynamic factor model contains the following set of equations representing a state-space form.

$$x_t = x_{t-1} + w_t \text{ where } w_t : MVN(0,Q)$$

$$y_t = Zx_t + a + v_t \text{ where } v_t : MVN(0,R)$$

$$x_0 : MVN(\Pi,\Lambda)$$

We estimate the DFM using a multivariate autoregressive state-space model[12]. The time-series of economic indicators (y) is modelled as a linear combination of the hidden trend (x) and factor loadings (Z) plus some offset 'a'. For example, the DF-6 model consists of IIP-consumer goods, non-oil and non-gold imports, domestic auto sales, rail freight, air cargo and government receipts represented by six observed time series. The model extracts the common underlying trend in the observed time-series as a single-index dynamic factor. The MARSS specification consists of two stochastic components: an unobservable common component, x_t and an idiosyncratic component v_t. Both of these components are modelled as autoregressive stochastic processes. x_t is an estimate of DFs and Z represents the loadings of the economic indicators on the common component. The identifying assumption in the above model is that the co-movements in the time series indicators arise from the single source x_t, i.e. x_t enters each indicators with different loadings, Z_i, i=1…. ,6. This is ensured from our assumption that v_{it} and x_t are mutually uncorrelated at all leads and lags for all the 6 observed economic indicators. The same model is estimated further by including three additional variables (DF-9) and six additional variables (DF-12). It is noted that all these three track actual GDP turning points quite closely.

An important issue is related to the choice of number of indicators in generating dynamic factors. While it makes sense to derive a dynamic factor based on a large set of economic indicators, typically 100 or more, however, from a policy point of view it is more meaningful to generate an economic activity index based on a set of shortlisted indicators. We have multiple rounds of screening procedure to weed out indicators that are either not significantly correlated with GDP series or not significantly relevant around turning points in GDP. A dynamic factor generated out of relevant indicators can accurately help us gauge the contribution made by activity indicators, especially identify indicators that are driving or dragging the dynamics in the common factor.

Next, we focus on the dynamics of DF-6 in the recent quarters. Chart 2 represents both year-on-year (Y-o-Y) and month-on-month (M-o-M) variation in DF-6. To iron out the monthly fluctuations, we present three-month moving average of
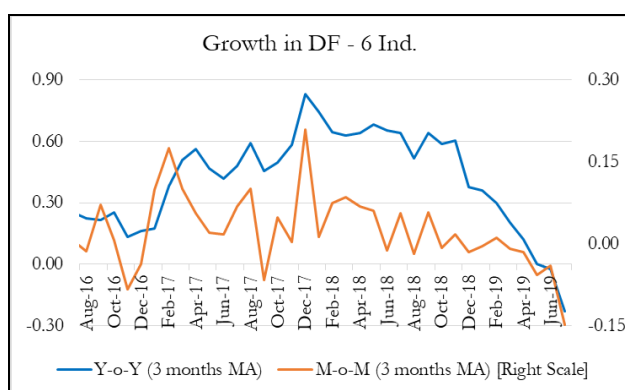

[12] The model is estimated using the MARSS package in R.

both the series. The M-o-M series indicates monthly momentum in economic activity while the Y-o-Y series captures the yearly dynamics. The M-o-M series suggests a sharp deceleration coinciding with the period of demonetization, and also a sharp recovery quickly thereafter. Subsequently, since early 2018, the monthly momentum suggests a gradual moderation in economic activity. The Y-o-Y series, like the monthly series, captures the demonetization downturn and the subsequent recovery, which peaked in December 2017, helped by the low base of the previous year. The Y-o-Y series also suggests economic deceleration as indicated by the M-o-M series since early 2018 (Chart 2).

Chart 2: DF-6, recent period dynamics

Chart 3: DF-6 augmented by GDP
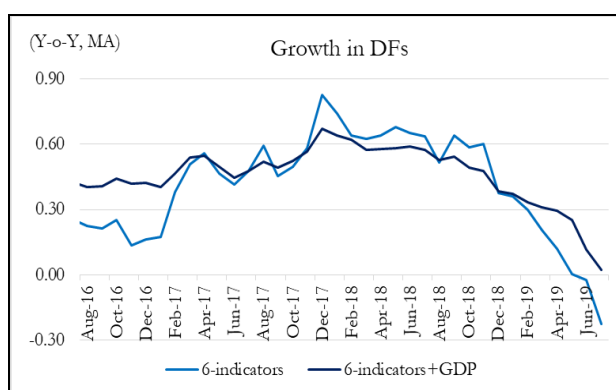
Ind.: Indicators

Some authors include GDP along with other high frequency indicators of activity to construct a coincident indicator (Dua *et al.* 1999). Following this, we also include GDP in DF-6 which is represented in Chart 3.[13] It is noted that the dynamics of DF-6 doesn't change considerably with/ without GDP and both indicate a downturn in economic activity in 2018-19.

Chart 4 plots the contribution[14] of each of the indicators included in the model to explain the variation in M-o-M (3 months MA) DF-6. We also report the contribution of each indicator in Table 2. It is evident that recent deceleration has been broad based. Both consumption indicators – auto sales and IIP-consumer goods, and investment indicators – rail freight and air cargo have contributed significantly in the recent deceleration.

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[13] In our sample, quarterly GDP is available until June 2019. The jagged edge methodology is used to handle the missing observations of GDP for recent months.

[14] Contribution of a component = M-o-M growth of component*Regression coeff. of M-o-M growth in component on M-o-M growth of DF.

Table 2: Contribution by Components

	Jan-19	Feb-19	Mar-19	Apr-19	May-19	Jun-19	Jul-19
IIP-cons goods	0.002	-0.009	-0.018	0.029	-0.007	-0.044	0.080
NONG imports	0.011	-0.015	0.004	-0.002	0.012	-0.023	0.025
Auto sales	0.033	0.002	-0.077	-0.003	0.032	-0.006	-0.067
Rail freight	-0.006	0.049	0.096	-0.025	-0.047	-0.031	-0.034
Air cargo	0.007	-0.043	-0.005	-0.041	0.006	-0.018	0.041
Govt. taxes	0.004	-0.003	0.001	0.032	-0.035	0.003	0.003
DF	**0.051**	**-0.018**	**0.001**	**-0.009**	**-0.039**	**-0.118**	**0.048**

Chart 4: Contribution by Components
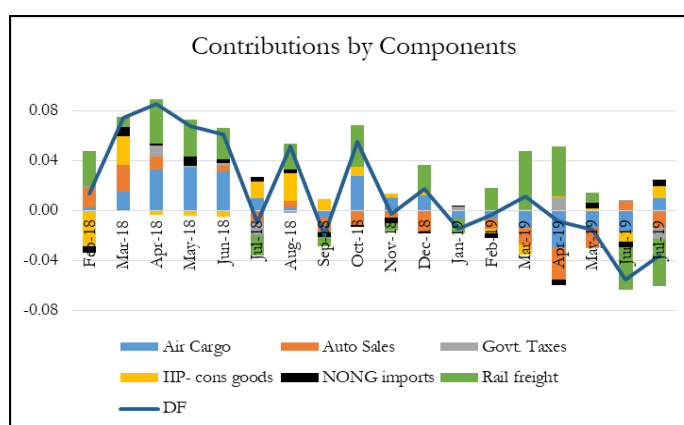
As indicated earlier, we expand our indicator list to include IIP-core, foreign tourist flows and exports. These additional variables represent investment and services activities. Chart 5 plots the recent dynamics of DF-9, which is in line with DF-6. It is noted that while broadly tracking economic activity well, DF-6 and DF-9 still miss some of the turning points, for example the quarter ending June 2017, which was impacted by Goods and Services Tax led disruption, and the extent of the recent slowdown (Chart 8). To address this problem in DF-6 and DF-9, we augment the model by including a financial block to improve the tracking of GDP growth, our target variable. While some of the financial variables might display leading properties and therefore deviate from the core principles of tracking contemporaneous economic activity, we still included Sensex, bank credit and NEER which are likely to better capture turning points (MSM No.10).[15] DF-12 points towards some recovery in economic activities, contrary to DF-6 and DF-9, in the recent times (Chart 6). This is on account of a sharp improvement observed in all financial indicators – bank credit, Sensex and NEER – in the recent period painting a somewhat optimistic picture of economic activity.

Chart 5: DF-9, recent period dynamics
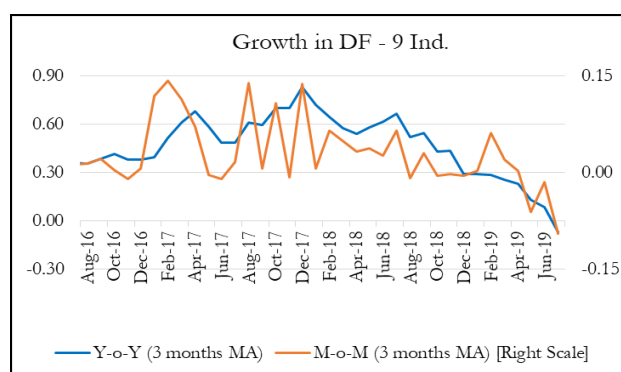
Chart 6: DF-12, recent period dynamics
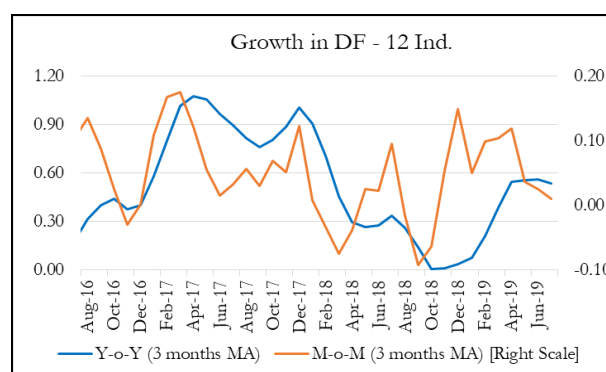
Ind.: Indicators.

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[15] https://www.rbi.org.in/Scripts/MSM_Mintstreetmemos10.aspx
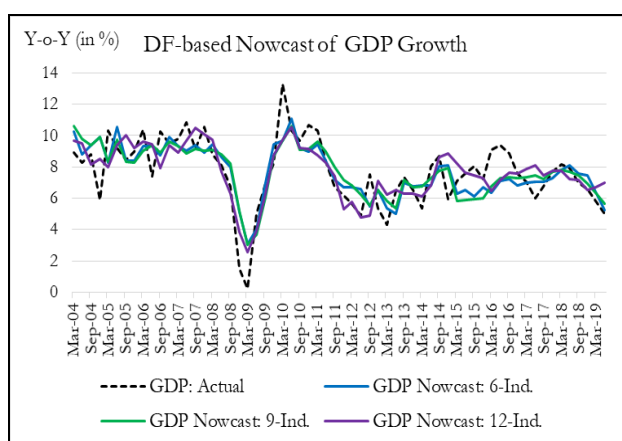
IV. 3. Nowcasting India's GDP Growth

Taking a cue from the literature, we use the estimated DFs to nowcast current quarter GDP growth well before (at least 8 weeks in advance) the official release. For this purpose, we estimate a parsimonious AR model of GDP growth augmented by DFs (Y-o-Y). The model estimates are presented in Table 3. The nowcasts based on 6, 9 and 12 indicator models along with actual GDP growth are plotted in Chart 7. It is observed that the GDP nowcasts track the actual GDP growth reasonably well over the estimation sample. It is also observed that the nowcasts were able to track the recent slowdown particularly well (Chart 8).

Table 3: Nowcasting Model Estimates

Dep. Variable	GDP (Y-o-Y)		
	Model 1 (6-Ind)	Model 2 (9-Ind)	Model 3 (12-Ind)
Constant	3.02	3.64	4.60
DF (Y-o-Y)	2.94	3.08	1.47
GDP (Y-o-Y), Lag 1	0.38	0.28	0.27
Model Diagnostics			
Adjusted R-squared	0.54	0.53	0.59
B-G Ser. Corr. LM Test	0.19	0.11	0.55
Out-of-Sample RMSE	0.61	0.65	0.98

Notes: 1. All coefficient estimates are significant at 1 per cent.
2. B-G test is for serial correlation in errors up to 12 lags.
3. Estimates are based on sample period 2004Q1 to 2019Q2.
4. Out-of-Sample RMSE pertains to 2017Q1 to 2019Q1.

Chart 7: GDP Growth and its Nowcasts

Chart 8: Recent Nowcasts
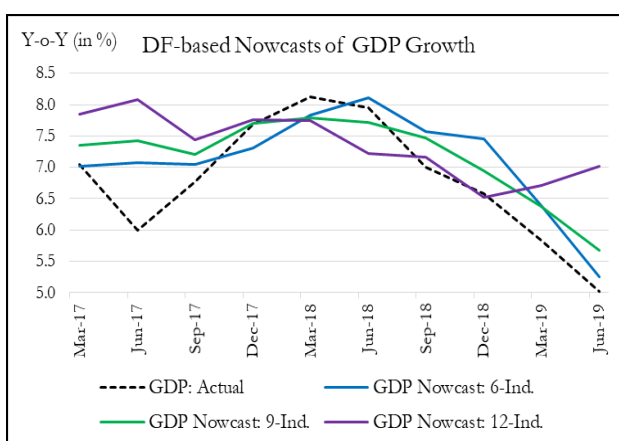
Ind.: Indicators.

IV.4. Model Performance

The next step in model building pertains to the evaluation of model performance. We estimate a parsimonious AR model of GDP growth augmented by DFs (Y-o-Y). Alternatively, we could have used multiple time series indicators in a

bridge equation framework to nowcast current quarter GDP growth. We prefer the former keeping in view the problem of overfitting. In time-series, we encounter the overfitting problem when the model starts to learn inherent idiosyncrasies in the training data to the extent that the performance of the model gets severely impacted on new dataset. This is only possible when the random fluctuation in the training sample gets picked up as a consistent pattern by the model and, thereby, hinders the model's ability to produce credible forecast/nowcast. One way to prevent the problem is to generate dynamic factors that can capture the common trend underlying several economic activity indicators. In other words, instead of fitting multiple time series indicators in a bridge equation framework to nowcast current quarter GDP growth, we prefer estimating a parsimonious AR model of GDP growth augmented by DFs.

Keeping in mind structural change (or crisis) in the economy, one should rely on the robustness of the model, and not just on optimization based on backfitting which works only for the past and is often suboptimal for the future. Accordingly, we examine the out-of-sample performance of the nowcasting models during 2017Q1-2019Q1. It is observed that the out-of-sample performance, measured in terms of root mean squared error (RMSE), is better for the DF-6 model compared to the DF-9 and DF-12 models (Chart 9 and Table 4).

We further examine forecast accuracy gains obtained from DF based growth nowcast estimates that have incremental information in the form of jagged edge data embedded in them. The high-frequency economic activity data releases in India are non-synchronous in nature. For example, monthly production of coal and crude oil is typically released on the last working day of the month, monthly production of commercial vehicles is released during the middle of a month, and railway freight traffic (of major commodities) is released during the first 10 days of every month. Also, there are varying lags in data releases. Together, this results in jagged-edge data. The out-of-sample performance suggests that DF-based nowcasts obtained from jagged-edge data structure perform marginally better than nowcast estimates obtained from data set without rough edges. The jagged-edge DF estimates consistently record a lower RMSE for 6, 9 and 12-indicator models compared to those without jagged edges.

Next, we apply mixed data sampling (MIDAS) regression to exploit the rich information contained in our monthly DFs to nowcast quarterly GDP and improve out-of-sample performance. We compare the models that adopt OLS method with those that use MIDAS method, which are specially equipped to handle mixed frequency data (details in Annex Note III). In general, the baseline DF-6 model performs better out-of-sample compared to DF-9 and DF-12 models. However, we

do not observe much of a forecast accuracy gains from applying MIDAS over OLS regression for DF-6, DF-9 and DF-12.

Chart 9: Out of Sample performance

Chart 9: Out of Sample performance
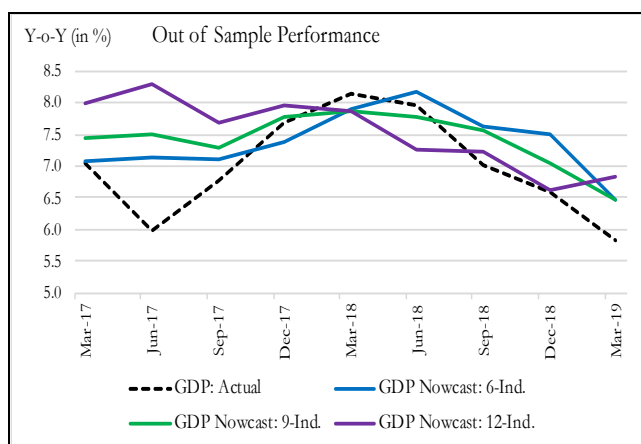
Table 3: Root Mean Squared Errors

Out of Sample (2017Q1-2019Q1) Performance: Root Mean Squared Error			
	MIDAS	Jagged Edge	
		Yes	No
6-Indicator	Yes	0.721	0.718
	No	0.609	0.616
9-Indicator	Yes	0.843	0.842
	No	0.651	0.654
12-Indicator	Yes	1.067	1.038
	No	0.980	0.982

To do a comparative analysis of GDP nowcast performance across different models, we report the out-of-sample performance of 6-indicator, 9-indicator and 12-indicator models. Table 3 reports the out-of-sample root mean squared error (RMSE) over the recent nine quarters i.e., 2017Q1-2019Q1. We compare the models that utilize dataset with jagged edges and use MIDAS with those that do not, for the 6-indicator, 9-indicator and 12-indicator models. The 6-indicator model using the jagged edge dataset records the lowest out-of-sample RMSE. Broadly, the analysis from using the jagged edge dataset seems to suggest that by exploiting the incremental information that is available from the actual flow of data releases, we are able to improve model performance.

We evaluate the performance of our model against that of the professional forecasters and market analysts. In this context, as mentioned in Section II, professional forecasters use their proprietary models, and they share their projections with Bloomberg. We plot the mean of such projections along with DF based nowcasts (Chart 10). In terms of forecast performance, DF-6 and DF-9 display accuracies comparable to that of the professional forecasters. In addition, DF based model is able to track turning points timely because it exploits the current flow of information available in high frequency indicators instead of only relying on a backward looking information set.

Chart 10: Nowcast Performance Evaluation vis-à-vis Market Projections
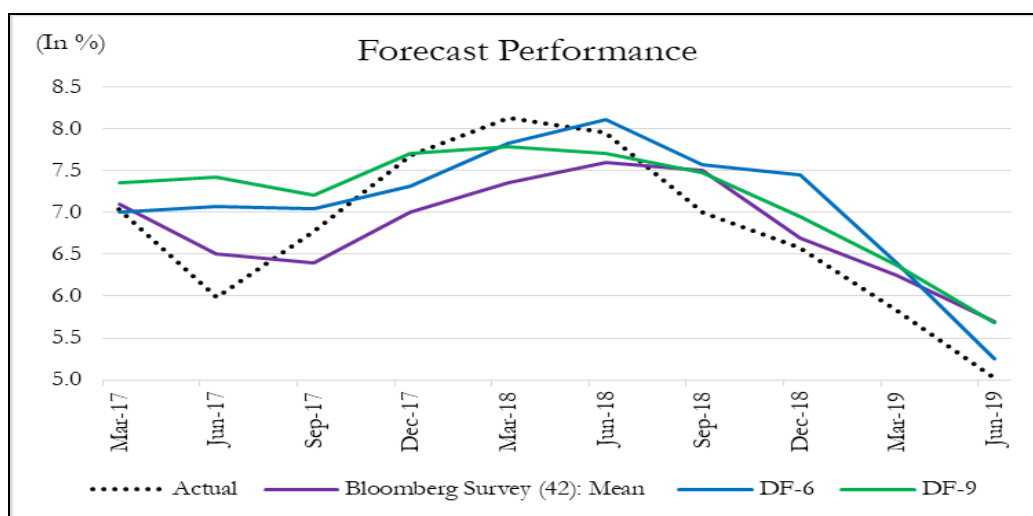
Finally, as a test of robustness, we compare the dynamics of DFs with an alternative and unconventional measure of economic activity captured in the nightlight data (luminosity index).[16] Notwithstanding the seasonality (September–October spike), limited availability (up to 2017) and aggregation problems (national average), luminosity index is expected to capture economic activities well, particularly in economies with dominant informal sectors. It is reassuring to note that Y-o-Y dynamics of DF-6 corresponds well with the nightlight data, which is provided by an independent source and is being extensively used of late (Chart 11).

Chart 11: Growth in DF-6 and Luminosity Index

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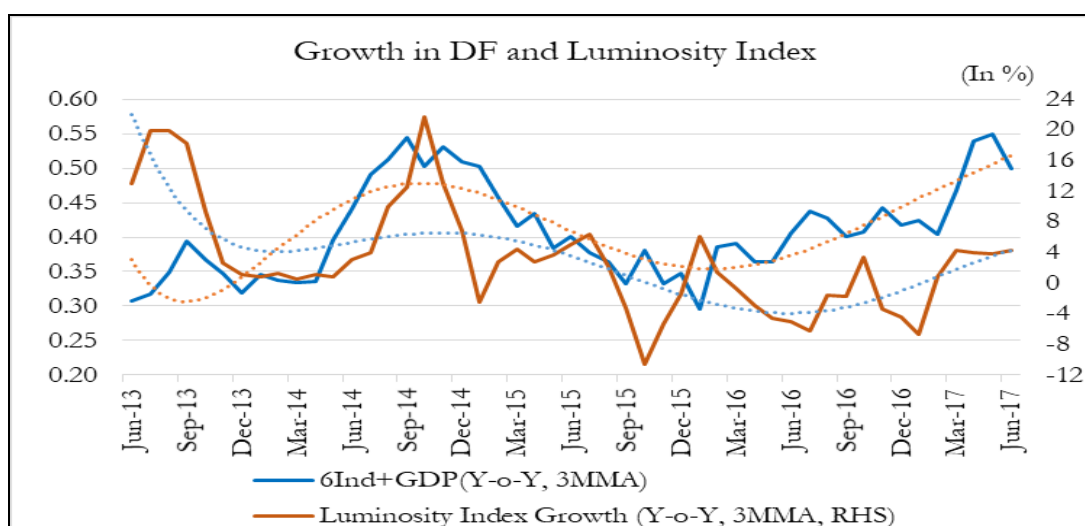
[16] Infrared Imaging Radiometer Suite (VIIRS) of National Aeronautics and Space Administration (NASA) and National Oceanic and Atmospheric Administration (NOAA), USA. VIIRS data has a wider radiometric detection range than former generation of similar satellites, which solves the issue of over-saturation at bright core centres (Elvidge *et al.* 2013). However, the publicly available VIIRS data still requires processing before use, as some temporary lights and background noise remain. We follow the procedure discussed in Beyer *et al.* (2018) and remove all observations from areas categorized as background noise mask. After outlier removal, these areas are identified by clustering the remaining observations based on their intensity.

V. Conclusion

A core concern in policy-making is identifying the signs of expansions and contractions in economic activity. At any point in time, diverse economic activity indicators may indicate mixed trends. Therefore, combining all of these together in an appropriate way to arrive at the underlying (or unobserved) trend has traditionally occupied the attention of both governments and businesses. Our aim has been to contribute to the existing literature by combining high frequency indicators, which are useful proxies of economic activity, to nowcast GDP growth of India.

To provide an early estimate of the current quarter GDP growth, we construct single-index dynamic factors using 6, 9 and 12 high-frequency indicators. These indicators represent various sectors, display high contemporaneous correlation with GDP, and co-move in line with the GDP turning points. While DF-6 includes domestic economic activity indicators, DF-9 combines indicators of trade and services and DF-12 adds financial indicators in the model. In addition to conventional economic activity indicators, we include a financial block in DF-12 to reflect the growing influence of financial sector on economic activity.

DFs are estimated using a dynamic factor model which extracts a common trend underlying the high-frequency indicators. The extracted trend provides a real time assessment of the state of the economy and helps identify sectors contributing to economic fluctuations. Further, GDP nowcast using dynamic factors show considerable gains in in-sample and out-of-sample accuracy. In particular, DF based nowcast is observed to closely track the recent slowdown in the Indian economy.

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Annex Table I: International literature on Nowcasting GDP

Institutions	Bank of England	Federal Reserve Bank of Atlanta (FRBA)	Federal Reserve Bank of New York (FRBNY)	European Central Bank	Norges Bank	Canada	Japan	Indonesia	Mexico
Blocs									
Industry and construction	Total Business Investment Housing Investment Construction Output Industrial Production Manufacturing Production PMI-Construction PMI-Manufacturing CIPS-E-Manufacturing CIPS-E-Construction CBI Industrial Trends CBI Distributive Trends Lloyds Business Barometer Agents' Score	Philly Fed Business Outlook Survey Chicago Fed Midwest Manufacturing Index ISM Manufacturing Index Industrial Production New Residential Construction C20 (Housing Starts) Manufacturers' Shipments, Inventories and Orders Construction Spending	Housing Starts Building Permits Value of Construction put in place Industrial Production Index Capacity Utilization Inventories: Total Business Merchant Wholesalers Inventories: Total Manufacturers' New Orders: Durable Goods Manufacturers' Shipments:Durable Goods Manufacturers' Inventories: Durable Goods Manufacturers' Unfilled Orders: All Manufacturing Industries Merchant Wholesalers Inventories: Total Inventories: Total Business Empire State Mfg. Survey: General Business Condition Phila.Fed.Mfg.Business Outlook: Current Activity ISM mfg.: PMI Coomposite Index ISM mfg.: Price Index	Industrial Production: Total Industry Industrial Production: Manufacturing New Orders: Manufacturing Working on Orders PMI-Manufacturing Industrial Confidence Indicator Retail Trade Confidence Indicator	PMI Industrial Production Turnover: Mining/Manufacturing Construction Output Capacity Utilisation Industrial Confidence Indicator New Orders: All Industries	Manufacturing Shipments	IIP Index of Tertiary Industry Activity Index of All Industry Activity Index of Construction Industry Activity Current Survey of Commerce (Sales Value, Wholesale) Survey of Production Forecast	PMI-Manufacturing	IMEF Business Climate Index-Manufacturing IMEF Business Climate Index-Non-manufacturing Producer Confidence Index Opinion Survey-Manufacturing Orders Total Vehicle Production Industrial Production Production of Crude Producer Confidence Index
Personal Income/ Consumption	Retail Sales Index Private Consumption	Reuters/University of Michigan Index Conference Board Consumer Confidence BEA Unit Auto Sales Existing Home Sales New Home Sales Personal Income and Sales	Real Personal Consumption Expenditure Real Disposable Personal Income New Single Family Houses Sold Retail Sales and Food Services	New Passenger Car Registration Consumer Confidence Indicator	Retail Sales Consumer Confidence	Retail Sales		Consumer Confidence Index Danareksa Consumer Confidence Local Auto Sales Motorcycle Sales	Consumer Confidence Index Automobile Sales Truck Sales Retail Sales
Employment	Claimant Count Rate LFS Number of Employees LFS Unemployment Rate	Initial Unemployment Insurance Claims Employment Situation	JOLTS Job Openings: Total ADP Nonfarm Private Payroll Employment Nonfarm Business Sector: Unit Labour Cost Civilian Unemployment Rate All Employees: Total Nonfarm	Unemployment Rate: Total Index of Employment: Total Industry	Employment Unemployment Rate	Monthly Payroll Employment			Unemployment Rate
Services	Index of Services CPIS-E-Services PMI-Services			Purchasing Managers Survey, Services: Business Activity Services Confidence Indicator					
External Sector	Sterling Effective Exchange Rate BOP Total Imports BOP Total Exports	International Trade	Exports: Goods and Services Imports: Goods and Services	Extra Euro Area Trade: Export Value Nominal Effective Exchange Rate: Core Group of Currencies against Euro	Merchandise Exports Merchandise Imports			Foreign Reserve Trade Balance Exports Net Foreign Assets Imports BoP Current Account Balance	Total Vehicle Exports Crude Exports Crude Imports Trade Balance
Prices		U.S. Imports Price Index U.S. Exports Price Index Producer Price Index Consumer Price Index	PCE: Chain Price Index PCE less Food and Energy: Chain Price Index CPI-U: All Items CPI-U: All Items less Food and Energy	HICP: Overall Index PPI: Excluding Construction Consumer Survey: Price Trend (12 months) Industry Survey: Selling price Expectation Raw Material, excl. Energy: Market Prices Raw Material, Crude Oil: Market Prices	CPI		PPI (deflator for Sales Value)	CPI CPI-Core CPI-NSA	
Miscellaneous Economic Activity	GDP	ISM Non-manufacturing Index Wholesale Trade Retail trade and inventories Manufactured Home Surveys	ISM Non-manufacturing: NMI Composite Index Real GDP	GDP: Chain Linked	GDP Mainland Norway	GDP	GDP Reuters Tankan DI (soft indicators) Economy Watchers Survey	GDP (YoY and QoQ)	
Credit and Finance	Mortgages Approved Net Consumer Credit UK Focussed Equity Index Term Spread Corporate Bond Spread	S&P 500 Index		M3: Index of National Stocks Index of Loans Dow Jones Euro Stoxx: Broad Stock Exchange Index Euribor 3 month				Bank Indonesia Reference Rate Money Supply (M1) Money Supply (M2)	
Methodology									
	Release-Augmented Dynamic Factor Model	Dynamic Factor Model Bridge Equation Approach	Dynamic Factor Model Kalman-Filtering Techniques	Dynamic Factor Model Kalman-Filtering Techniques	Bayesian Dynamic Factor Model	Dynamic Factor Model Kalman-Filtering Techniques	Dynamic Factor Model Mixed Data Sampling	Dynamic Factor Model	Dynamic Factor Model Expectation- Maximization Algorithm

# Annex Table II: Nowcasting literature for India

Institutions	RBI(CEII-6)	RBI(CEII-9)	RBI(CEII-12)	Bloomberg	Rabobank	NIPFP (2011)	Dalhaus et al (2017)	Bragoli and Fosten (2016)	Dua and Banerjee (1999)	RBI (2006)
Blocs				Regularly Updated			One Time Study			Group Report
Industry and construction		IIP-Infrastructure	IIP-Infrastructure	Industrial Production Capital Expenditure Index Construction Index	PMI-Manufacturing Electricity Production IIP Crude and Steel Production	IIP-Mining IIP-Manufacturing IIP-Electricity Production of Coal and Crude Production of Cement and Steel Commercial Vehicle Production	PMI-Manufacturing IIP-Basic Metal IIP-Electricity	IIP PMI-Manufacturing Production of Crude Production of Steel Electricity Generation Industrial Performance Assessment	Industrial production of consumer goods	IIP-General Index IIP-Basic Metal IIP-Electricity IIP-Intermediate Goods Production of Commercial Motor Vehicle Cargo Handled in Major Ports
Personal Income/ Consumption	IIP-Consumer Goods Auto Sales	IIP-Consumer Goods Auto Sales Petroleum Product Consumption	IIP-Consumer Goods Auto Sales Petroleum Product Consumption	Auto Sales Petroleum Product Consumption	Vehicle Sales Car Passenger Registration Personal Loans Petroleum Product Consumption	Cellular Subscription				
Employment									Monthly Registered Unemployed	
Services	Government Tax Revenue	Government Tax Revenue	Government Tax Revenue		PMI-Services Net Tax Revenue	Central Government Revenue Expenditure				
External Sector	Non-Oil and Non-Gold Import	Non-Oil and Non-Gold Import	Non-Oil and Non-Gold Import	Agricultural Trade Balance	Vehicle Export		Exports Imports REER	Exchange Rate (INR/USD)		Exports Non-Oil Imports
Prices					CPI	WPI	CPI WPI Petrol Spot Price (Brent) World Commdity Price Index	CPI-Industrial Worker CPI- Agricultural Labourers CPI-Rural Labourers WPI-All Items		WPI: Industrial Raw Materials WPI: Manufactured Products Gold Prices in Mumbai
Miscellaneous Economic Activity	Rail Freight Air Cargo	Rail Freight Air Cargo Foreign Tourist Arrival	Rail Freight Air Cargo Foreign Tourist Arrival	Foreign Tourist Arrival Traffic Index	Volatility Index Railway Freight Earnings	Railway Goods Traffic Port Traffic	ISM Composite Index S&P 500 Composite Index	US Industrial Production US ISM PMI-Manufacturing Euro Area 19 Industrial Production Euro Zone PMI-Manufacturing Asia Sentix Overall Index	GDP at factor cost interpolated to a monthly series Wages to worker in factory sector	US GDP US Leading Indicator Index Euro Area Leading Indicator Index
Credit and Finance				Real Currency Demand Real Combined Credit	Industry Loans Services Sector Loans MIBOR BSE-500 BSE-Sensitive Index Monetary Base (M0)	Non-Food Bank Credit Deposits NSE Turnover	Money Supply NSE-500 91-day Tbill 10 Year Bond Yield FOMC-Fed Fund Target Rate	Money Supply (M1) 91-day Tbill Sensex BSE 30		Broad Money (M3) Real M3 (M3/WPI) Currency with Public Bank Credit Forward Premia 6-month
Methodology										
	Dynamic Factor model Mixed Data Sampling	Dynamic Factor Model Mixed Data Sampling	Dynamic Factor Model Mixed Data Sampling	Weighted Average of Monthly Activity Indicators	Bayesian VAR Ordinary least squares Combined model	Bridge Equation Models	Dynamic Factor Model	Dynamic Factor Model		Dynamic Factor Analysis Turning Point Analysis Cross-Correlation Analysis

Annex Table III: Dynamic cross-correlation for indicator selection

Indicators	GDP$_{(t-1)}$	GDP$_{(t)}$	GDP$_{(t+1)}$	Indicator Type
Agri Wages	-0.03	0.07	-0.12	X
Air Cargo	0.17	**0.37***	**0.27***	C
Air Passenger	**0.33***	**0.28***	**0.31***	C/L-
Auto Commercial	0.08	**0.41***	**0.43***	C/L+
Auto Passenger	**0.25***	0.17	0.18	L-
Auto Total	0.17	**0.25***	**0.24***	C
Bank Credit	0.11	0.08	-0.09	X
Cement	0.04	0.12	0.11	X
CPIIW	0.11	-0.05	-0.06	X
CRBComm	**0.33***	**0.44***	0.13	C
Crude Indian Bas	0.19	**0.37***	-0.02	C
Exports	**0.31***	**0.35***	-0.02	C
Foreign Tourist	0.19	**0.36***	0.12	C
Forex	**0.28***	**0.27***	**0.29***	C/L+
Govt Receipts	**0.21***	0.10	-0.01	L-
IIP Consumer	**0.20***	**0.54***	-0.01	C
IIP Core	**0.25***	**0.20***	**0.28***	L-/C/L+
NEER	0.14	**0.24***	0.15	C
NONG Imports	**0.33***	0.19	-0.02	L-
OECD Ind Prod	**0.40***	**0.43***	0.04	C/L-
Oil Consumption	0.14	0.15	-0.02	X
Power Demand	-0.01	**0.37***	-0.14	C
Rail Freight	**0.20***	0.17	0.15	L-
Rail Passenger	-0.01	0.15	0.03	X
Sensex	**0.25***	**0.52***	**0.23***	C
Steel	0.20	0.11	0.12	X
TBill91D	0.13	0.16	-0.05	X
VIX	-0.03	**-0.30***	**-0.26***	C

*: Indicates 5 per cent level of significance; C: Cotemporaneous, L+: Leading & L-: Lagging indicators.

Annex Note I: Replication of Dua and Banerji (1999)

Standardized Cycles in Indian Economy (Dua and Banerji 2000)
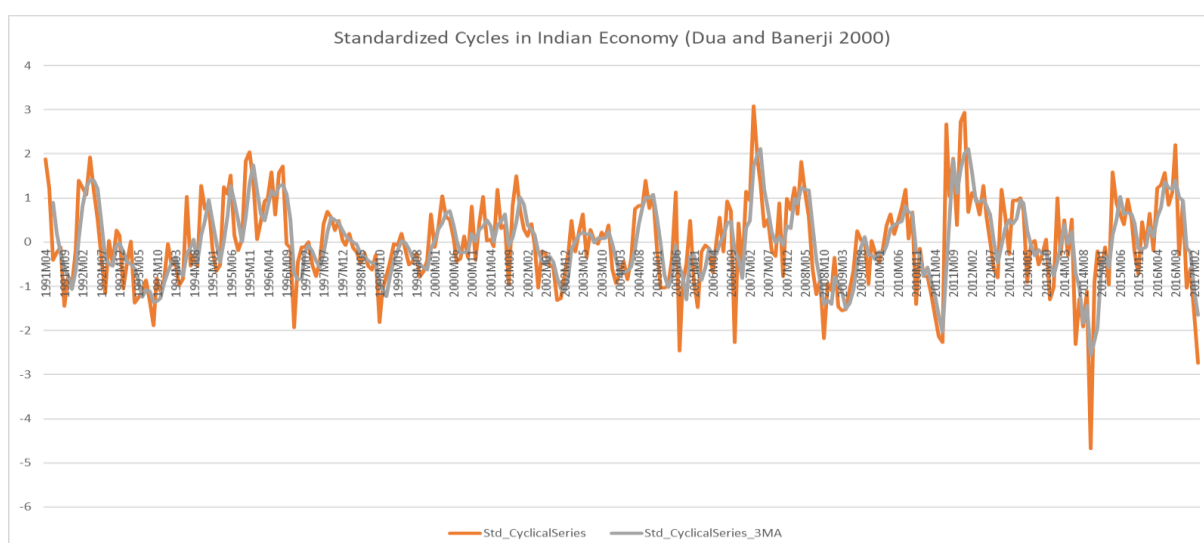
Step involved in replication and updating

1. All data monthly, and seasonally (Census X-11) adjusted

   a. We use Census X-12 instead. We also obtain the cyclical component of the log deviation of each series by applying an H-P Filter (λ = 14400). We then standardize each cyclical series using their respective standard deviations.

2. Output: Two different measures of CEI which correspond to the following two different variables for output:

   a. <u>Real GDP at Factor cost</u>: Das (1993) has quarterly data on GDP for the period 1970-91. This is interpolated to 1950. Monthly data - dividing quarterly data by 3.

   b. Closely follow Banerji and Dua (2000), and obtain monthly GDP series using the procedure given in Das (1993). For data from 2012-13, we use the Real GVA at FC

3. <u>Index of Industrial Production</u>: Monthly data available

   a. We do not report results using IIP for our exercise (also not reported in Banerji and Dua (1999)).

4. Income: Annual wage data from the ASI are interpolated into monthly data using a monthly adjustment factor.

   a. <u>The Adjustment Factor</u>: the adjustment factor = [monthly variation in the consumer manufacturing output relative to an annual average] X [relative volatility of annual wages and annualized consumer manufacturing output]

b. The closest data available is annual compensation of employees, from 1991 from the EPW-Research foundation. This is collated from ASI.

Employment: Monthly seasonally adjusted unemployment numbers from the Monthly Abstract of Statistics (MAS)

c. This data is available only until Dec-2013. MAS is no longer published. One option is to collate all the previous MAS and forecast present data using suitable forecast methodology.

d. We use the total labor force data and multiply this with the annual unemployment rate – available with world bank from 1991 – to obtain the annual unemployment data. We then follow the same interpolation used by Banerji and Dua (1999) to obtain the monthly unemployment series.

5. Trade: In this paper, trade is all domestic. Industrial production of consumer goods at constant prices and seasonally adjusted.

6. Data on actual production levels are not available. We therefore use monthly consumer goods IIP – after necessary splicing to get monthly series at the 1980-81 base.

Annex Table IV: 9-indicator Model: Components and Contribution

	Jan-19	Feb-19	Mar-19	Apr-19	May-19	Jun-19	Jul-19
IIP-cons goods	0.001	-0.004	-0.008	0.014	-0.002	-0.022	0.036
NONG imports	0.005	-0.007	0.002	-0.001	0.006	-0.011	0.012
Auto sales	0.016	0.001	-0.036	-0.002	0.015	-0.003	-0.031
Rail freight	-0.003	0.023	0.045	-0.011	-0.022	-0.014	-0.016
Air cargo	0.003	-0.020	-0.002	-0.019	0.003	-0.008	0.019
Govt. receipts	0.002	-0.002	0.001	0.015	-0.016	0.002	0.001
Exports	0.018	-0.009	0.047	-0.052	0.048	-0.086	0.065
Foreign Tourists	0.014	0.006	-0.040	0.030	-0.063	0.089	-0.034
IIP-core	0.018	0.018	0.093	-0.023	-0.022	-0.024	0.051
DF-9	**0.074**	**0.007**	**0.101**	**-0.048**	**-0.054**	**-0.077**	**0.102**
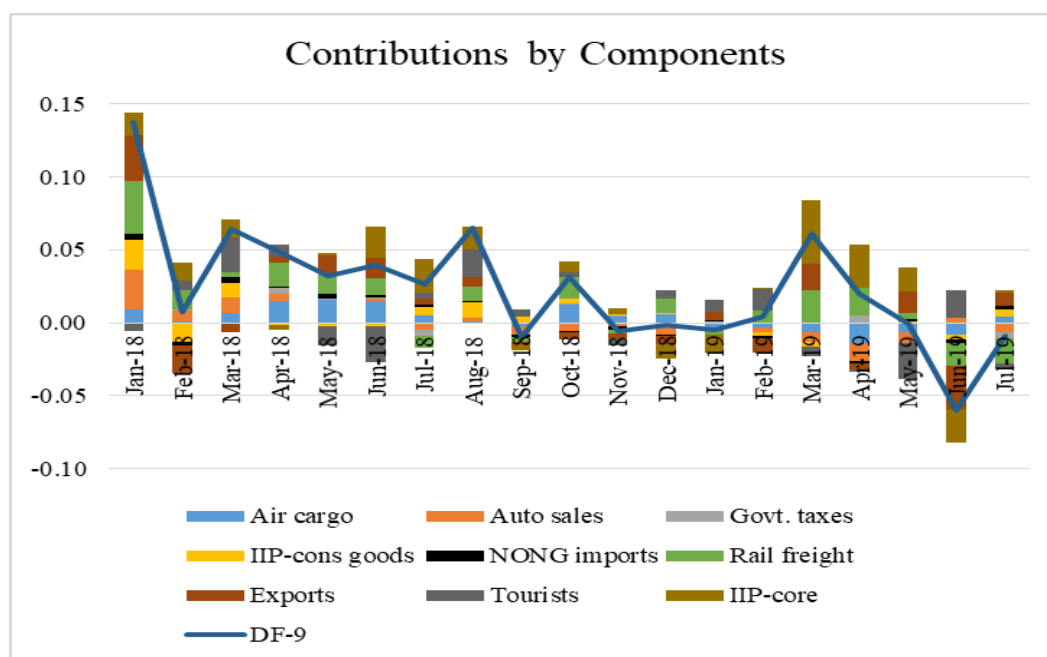
Annex Note III: MIDAS

The explanatory variables can also have frequencies different from each other. The basic equation for MIDAS is similar to that of distributed lag models, exhibiting a dynamic relationship between the dependent and independent variables. However, there are still significant differences between the two methods. The basic equation for MIDAS is (Ghysels *et al.* 2004):

$$Y_t = \beta_0 + B\left(L^{\frac{1}{m}}\right)X_t^{(m)} + \epsilon_t^{(m)}$$

Where $B\left(L^{\frac{1}{m}}\right) = \sum_{j=0}^{jmax} B(j)L^{j/m}$ is a polynomial of length j^{max} in the $L^{1/m}$ operator and the $L^{j/m}$ operator lags $X_t^{(m)}$ by j/m periods. We can run the above non-linear regression to estimate the dependent variable. Extracting the maximum information from the dataset, requires a suitable polynomial and a suitable polynomial may involve an increased number of lags of $X_{(t-j)}^m$ data. This requires estimating many parameters and is one of the shortcomings of MIDAS (Ghysels *et al.* 2004).